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Universal patterns in color-emotion associations are further shaped by linguistic and geographic proximity

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Significance statement

Why do we see red, feel blue, or turn green with envy? Are such associations between color and emotion fundamental to our shared cognitive architecture? Or are they cultural creations learned through our languages and traditions? To answer these questions, we tested the emotional meaning of colors in 4598 participants from 30 nations, in 22 languages. Overall, participants associated similar emotion concepts with 12 color terms. Moreover, similarity was higher between nations that share borders or languages. Color-emotion associations have universal features, further shaped by a shared language and / or geography. These results pose further theoretical and empirical questions about the affective properties of color, and may inform practice in applied domains such as well-being and design.

Abstract

Many of us see red, feel blue, or turn green with envy. Are such color-emotion associations fundamental to our shared cognitive architecture, or are they cultural creations learned through our languages and traditions? To answer these questions, we tested emotional associations of colors in 4598 participants from 30 nations, speaking 22 native languages. Participants associated 20 emotion concepts with 12 color terms. Pattern similarity analyses revealed universal color-emotion associations (average similarity coefficient r = .88). But, local differences were also apparent. A machine learning algorithm revealed that nation predicted color-emotion associations above and beyond those observed universally. Similarity was greater when nations were linguistically geographically or close. This study highlights robust universal color-emotion associations, further modulated by linguistic and geographic factors. These results pose further theoretical and empirical questions about the affective properties of color, and may inform practice in applied domains like well-being and design.

Abstract word count: 146 words (max 150)

Keywords: Affect; color perception; cross-cultural; universality; cultural relativity; pattern analysis

Word count: 5379 (all) / 1888 (counted) words (max 2000 words for introduction, discussion, footnotes, and acknowledgments, 40 references).

Introduction

Color-emotion associations are ubiquitous (Adams & Osgood, 1973; Hupka et al., 1997; Madden et al., 2000; Major, 1895; Palmer et al., 2013; Valdez & Mehrabian, 1994; Wexner, 1954; Wilms & Oberfeld, 2018). Common wisdom would suggest that we feel blue when sad, see red when angry, and are green with envy. Yet, envy can be yellow or red if we come from Germany or Poland, respectively (see Hupka et al., 1997). And while westerners are likely to wear white to weddings and black to funerals, people from China prefer red for weddings and white for funerals. Wherever one comes from, such color-emotion associations are intriguing because colors and emotions seem at face value to be fundamentally different . Colors are visual experiences driven by the wavelength of light. Emotions are subjective feelings, cognitions, and physiological responses that signal value. Are these cross-modal associations cultural creations, laid down in our languages and traditions? Or are they fundamental features of our cognitive architecture? Existing studies have identified both similarities (Adams & Osgood
and differences (Hupka et al., 1997; Madden et al., 2000; Soriano & Valenzuela, 2009) across cultures. However, they have done so between only a small number of individual countries, making it nearly impossible to capture global patterns. In a series of analyses, we examined to what extent color-emotion associations are universal, testing 4598 participants from 30 nations on 6 continents in 22 languages.

There are two theoretical explanations for color-emotion associations, which make different predictions about the degree to which the emotional meanings of color should be shared. According to the first view, color-emotion associations arise through environmental experiences. That is, colors may become associated with emotions because they appear in particular emotional situations of evolutionary significance (e.g., red face in anger; Benitez-Quiroz, Srinivasan, & Martinez, 2018). If so, color-emotion associations should be largely universal (in support, see
Ou et al., 2018). According to the second theoretical explanation, colors and emotions may become arbitrarily associated in the
so, color-emotion associations should vary between cultures with different languages, symbolism, and traditions (Evarts, 1919; Soriano & Valenzuela, 2009). Such cross-cultural variations have also been reported (Hupka et al., 1997; Madden et al., 2000; Soriano & Valenzuela, 2009). While these views are often cast in opposition to each other, they are not mutually exclusive. According to the cross-modal correspondence framework (Spence, 2011), two unrelated entities (here, colors and emotions) can become cross-modally associated
or linguistic environment, whether on a global (shared by all) or local (shared by some) scale.

It is possible, therefore, that universal tendencies to associate certain colors with certain emotions are further modulated by cultural and individual factors. Consider red, an ambivalent color that has been associated with both negative and positive emotions, depending on whether one comes from Western countries or China (Jonauskaite, Wicker, et al., 2019). The existence of both associations could be explained in evolutionary terms (e.g., red-blood pairings lead to associations with both danger and sexuality).In some countries like China, however, cultural beliefs that red is a symbol of good fortune might strengthen the link between red and positive emotions and weaken the link between red and negative emotions (see Wang, Shu, & Mo, 2014). In other countries, like the USA, the strong link between red and danger or failure could strengthen negative while weakening positive associations (Pravossoudovitch et al., 2014). Such additional variations might be maintained through language and geographic locations (see also Jackson et al., 2019; Jonauskaite, Abdel-Khalek, et al., 2019).

Existing studies provide examples of both similarities
Egan, 1974; Gao et al., 2007; Ou et al., 2018) and differences (Hupka et al., 1997; Madden et al., 2000; Soriano & Valenzuela, 2009) across countries. But these studies have focused on just a few countries, languages, or cultures, and so global patterns are still unknown. To test for the degree of universality, we performed a large-scale, cross-cultural survey on color-emotion associations (for theoretical motivation, see Mohr, Jonauskaite, Dan-Glauser, Uusküla, & Dael, 2018). Participants completed the survey in their native language online. We exceeded previous investigations in terms of the number of tested nations, representativeness of participants, and the number of tested colors and emotions. We collected data from 4598 participants from 30 nations, located on all continents but Antarctica (Fig 1). Participants were aged between 15 and 87 years old and had normal color vision. We used 12 color terms representing the most common color categories (Berlin & Kay, 1969; Mylonas & MacDonald, 2015) and an extensive list of 20 emotion concepts varying in valence and potency (Scherer, 2005). Participants chose as many emotion concepts as they thought associated with a given color term and rated the intensity of the associated emotion from weak to strong.

In a series of analyses, we examined the degree of similarity across the 30 nations in probabilities of color-emotion associations and intensities of associated emotions. We then applied a machine learning algorithm to quantify the degree of nation-specificity in color-emotion associations. Finally, we assessed how color-emotion associations varied as a function of linguistic and geographic distances.

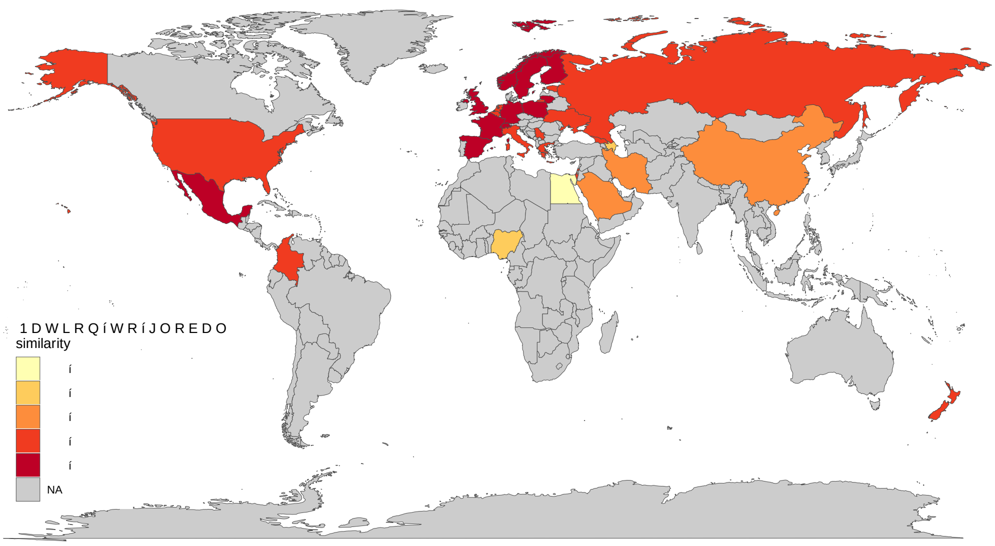

Fig 1. The world map of the 30 studied nations. The map is colored by nation similarity with the global color-emotion association pattern. Redder nations show color-emotion association patterns more similar to the global mean (also see Fig 4 A).

Materials and methods

Participants

We extracted our data from the ongoing International Color Emotion Association Survey (Mohr et al., 2018), performed online. This survey tests participants from a large age range using pre-defined age categories (15-29 years, 30-49 years, 50+ years). We started with the largest possible participant pool (N = 4883) consisting of data sets from countries for which we had at least 20 useable (e.g., without self-reported problems of color vision) participants per age category (see also, Simmons, Nelson, & Simonsohn, 2011). We detail additional selection criteria under Data preparation. Our final sample (n = 4598, 1114 males) consisted of participants from 30 different nations (Fig 1) with a mean age of 35.4 (SD = 14.5). Counts per nation ranged from 69 to 490 participants. Table S 1 provides language information and Table S 2 provides demographic information of the participants of each nation. Participation was voluntary. The study was conducted in compliance with the ethical standards described in the Declaration of Helsinki. Parts of the data have been reported previously in relation to different research questions (Jonauskaite et al., 2020; Jonauskaite, Abdel-Khalek, et al., 2019; Jonauskaite, Wicker, et al., 2019).

Material and Procedure

Emotion assessment with the Geneva Emotion Wheel (version 3.0, Fig 2 (Scherer, 2005; Scherer et al., 2013)). The Geneva Emotion Wheel is a self-report measure designed to assess the feeling component of emotional experiences elicited by particular events. It is based on theoretical categorizations of emotions and validated through research. The Geneva Emotion Wheel represents 20 discreet emotions (e.g., anger, fear, joy) as spokes on a wheel. Emotion concepts that are similar in valence (positive/negative) and power (high/low) are placed close to each other. Each spoke of the wheel contains five circles that extend from a central square, representing increasing intensities of each emotion.

For each color term, participants used a mouse click to indicate the associated emotions and their intensities (that is, they could indicate that a single color term is associated with more than one emotion concept, see Fig 2). At the beginning of the trial, the central square was selected,

-up window in which they could type the name of a different emotion. These responses were rare, and we did not analyze them.

Participants completed the Geneva Emotion Wheel in their native language. The translation of the Geneva Emotion Wheel was available for some languages on the Swiss Centre for Affective Sciences website. The remaining translations were created using the back-translation technique (see section Translation of the Geneva Emotion Wheel in Supplementary Material for further details). See Table S 3 for emotion terms in each language.

Fig 2. The Geneva Emotion Wheel with the color term red as an example. The wheel was used to assess associations between 20 emotion concepts and 12 color terms. Participants expressed emotion associations by selecting one of the five circles of each of the associated emotion. At the same time, they chose the intensity of the associated emotion, ranging from weak (smallest circle) to strong (largest circle). Participants could select as many or as few emotions as they thought appropriate. The right panel exemplifies a potential response from a participant for the color term red associated with strong love and relative strong anger.

International Color-Emotion Association Survey (http://www2.unil.ch/onlinepsylab/colour/main.php). We collected the current data online by sharing the survey link with potential participants via university communications, e-mails, social media, and personal contact, mainly through our collaborators (co-authors) in each country. The survey was originally constructed in English, and was translated (without back-translation) by co-authors and collaborators (see Acknowledgments section). We used links that automatically opened in the official language of the country to encourage participants to complete the survey in their native language. However, participants could switch to any other language provided. We only analyzed data gathered from native speakers. Online data collection naturally resulted in literate participants with access to the Internet. Some elderly participants were helped with survey completion.

The first page described the aims of the study and ethical considerations; participants

The following two instruction pages explained the task and the use of the Geneva Emotion Wheel. We then used a manipulation check to verify that participants understood the task. Participants were presented with a situation and

Peter thinks that beige strongly represents intense compassion, and believes that beige is also associated with mild relief. Accidentally, he has selected sadness and wants to correct his choice. Look at his response in the emotion wheel below and try to correct it

sadness marked (emotion intensity 5). They could only move to the next page and start the survey if

sadness (no association, rating 0), the largest circle for compassion (emotion intensity 5), and the middle circle for relief (emotion intensity 3). If participants made a mistake and tried to move forward, a pop-up window guided them to the correct responses. This manipulation check ensured that participants understood the task.

In the actual task, participants were presented with 12 color terms (not color patches): red, orange, yellow, green, blue, turquoise, purple, pink, brown, black, grey and white (see Table S 4 for the color terms in all languages). Color terms appeared one at a time above the Geneva Emotion Wheel in randomized order. For each color term, participants could select any number of the emotion concepts they thought were associated with the given color term, or indicate none. They rated the intensity of each chosen emotion (Fig 2). On average, participants associated 3.05 emotion concepts with a color term (95% CI =[3.03 3.08]; range = 2.25 3.84, see Table S 5).

After evaluating the 12 color terms, participants completed a demographic questionnaire in which they reported their age, sex, color blindness, importance of color in their life, country of origin, country of residence, native language, and fluency of the language in which they completed the color-
option for any of the demographic questions. On the final page, participants were thanked and received results from a previous, related study in a graphic form. We provided an e-mail address for future contact. The survey took 31 minutes on average to complete for the current sample (survey access: http://www2.unil.ch/onlinepsylab/colour/main.php).

Data preparation

We applied the following inclusion and exclusion criteria to clean the data. We included participants who i) finished the survey, ii) completed the survey in their native language, and iii) this language was the official language of their country of origin. Taking Norway as an example, we included native Norwegian speakers who completed the survey in Norwegian (Bokmål) and their country of origin was Norway. An exception was made for participants from Nigeria, who completed the survey in English (national language). Nigerian participants had high English proficiency levels (M = 7.02, SD = .29, out of 8; see Table S 1 for other languages and countries). As we stated above, we excluded participants who might have been color-blind by self-

color-blind participants across all the nations.

Statistical analyses

With 20 emotion concepts and 12 color terms, we obtained 240 ratings of color-emotion associations per participant. From these associations, we extracted two dependent variables. The first dependent variable was the probability of color-emotion associations. The second dependent variable was emotion intensity (see below). The alpha level was set to .050 for all statistical analyses. Statistical analyses were performed and graphs created with SPSS v.25 and R Studio v. 1.1.4 (R version 3.4.0).

Global probabilities. To evaluate the probability of color-emotion associations, we assessed which emotion(s) are associated with each color term without considering emotion intensity. To this end, all selected emotion associations were coded as 1 (regardless of intensity), and all non-selected emotion associations were coded as 0. We used a Bayesian method to estimate probabilities of each emotion being associated with each color term (see section Bayesian probabilities in Supplementary material). We used the mean estimated probabilities of all participants for each color-emotion pair to construct a global matrix of color-emotion association probabilities (12 20; Fig 3). The same procedure was repeated for each of the 30 nations separately to obtain mean probabilities of associating every emotion with every color term in each of the 30 nations (see 30 nation-specific color-emotion association matrices in Table S 6). We used nation-specific matrices for further cross-cultural comparisons.

Cultural probabilities and their comparisons. We first determined the degrees of similarity between nation-specific patterns of color-emotion associations and the global pattern of color-emotion associations nation-to-global pattern similarity. The underlying values were Bayesian probabilities. The degrees of similarity were calculated by computing correlations between the 12 20 color-emotion association probabilities of each nation (nation-specific matrix) and the corresponding global 12 20 color-emotion association probabilities (global matrix without that nation). The global probabilities were always based on data from 29 nations, that is, all nations but the nation of comparison. These 30 global matrices including the data from 29 nations correlated from .9983 to .9993 with the global matrix including the data from all 30 nations. Hence, no single nation unduly influenced the global pattern. See the full list of nation-specific and global matrices in Table S 6. Next, we estimated nation-to-nation pattern similarity by correlating all nation-specific matrices with each other (900 matrix correlations, Table S 7). We also looked at the effects of sex (Table S 8) and age (Table S 9), reported in the Results sub-section Socio-demographic factors. Finally, we repeated the pattern similarity analyses per color term. That is, we correlated nation-specific patterns of color-emotion association probabilities with global patterns excluding that nation for each color term (e.g., nation-specific pattern of red vs. global pattern of red, excluding that nation; Table S 10). In all of these comparisons, a score of 1.0 indicates perfect color-emotion association pattern similarity, while a score of 0.0 indicates complete color-emotion association pattern dissimilarity.

In addition to color-emotion association pattern similarity, we calculated the average probabilities of associating any color with any emotion color-emotion association average probability. The nation-specific color-emotion association average probability was calculated by averaging all the 240 Bayesian probabilities of color-emotion associations of each nation. The unweighted global color-emotion association average probability was calculated by averaging all nation-specific color-emotion association average probabilities (global average probability score = .161, 95% CI =[.150-.174]). We compared the global color-emotion association average probability with nation-specific color-emotion association average probabilities using one-sample t-tests. To account for multiple comparisons, p-values were FDR corrected, using q = 0.05 as threshold. As in the pattern similarity analyses, we repeated the comparisons per color term as well as for sex and age (see the Results sub-section Socio-demographic factors). A color-emotion association average probability score of 1.0 indicates that all color terms were associated with all emotion concepts, while a score of 0.0 indicates that no color term was associated with any emotion concept.

The emotion intensity variable provides information about the average intensity of all emotions associated with each color term. To calculate emotion intensity similarities, we took all emotion concepts associated with a given color term (previously coded as 1) by a given participant and averaged the intensities assigned to these emotions. Emotion intensities are reported per color term and not per color-emotion association. They varied from 1 (weak) to 5 (intense), unless no emotion was chosen for a given color term (coded as missing value). We had 12 emotion intensity scores per participant (one score per color term) and compared these scores across nations. We computed between the 12 emotion intensity scores of each nation and the corresponding global emotion intensity scores, each time leaving out that nation, when calculating nation-to-global emotion intensity similarities (see Table S 11). The resulting 29 global emotion intensity matrices including the data from 29 nations correlated from 0.9967 to 0.9999 with the global emotion intensity matrix including the data from all 30 nations. Hence, no single nation unduly influenced the global pattern. An emotion intensity similarity score of 1.0 indicates perfect emotion intensity pattern similarity, while a score of 0.0 indicates complete pattern dissimilarity.

Multivariate pattern classification. We used a supervised machine learning approach to predict the nation of each participant from his or her set of 240 ratings of color-emotion association (also see, Jonauskaite, Wicker, et al., 2019). The accuracy of the classifier provides a quantitative measure of nation-specificity in color-emotion associations. If the accuracy is equal to chance, this indicates an absence of nation-specificity in the color-emotion associations (i.e., perfect universality). In contrast, high accuracy indicates a high degree of nation-specificity. For details of the classifier algorithm, fitting and evaluation, see Multivariate pattern classification in Supplementary material.

A quantitative measure of the similarity between a pair of nations in terms of their color-emotion associations can be readily computed from the classifiers' confusion matrix, based on the assumption that nations that are more similar will be more frequently confused by the classifier than nations that are less similar. We used Luce's biased choice model (Eq. 5 in Luce, 1963) to estimate similarity values for each pair of nations from the confusion matrix. By convention, a similarity value between a nation and itself is set to 1.0 (representing maximum similarity), while a similarity value of 0.0 means that the two nations are completely dissimilar. The estimated similarity values are displayed in Fig S 1.

Linguistic and geographic distances. In addition to assessing cultural similarities, we tested whether two factors linguistic distance and geographic distance explain part of the similarity between the color-emotion associations of different nations. We extracted linguistic distances for each nation-nation pair from Jäger (2018) (see Linguistic distances in Supplementary Material for language codes). These distances are suggested to capture phylogenetic distances that quantify the degree of similarity between the languages of our nation pairs.

The linguistic distances in Jäger (2018) range from 0 to 1, with lower linguistic distance scores indicating higher linguistic similarities. In this dataset, the linguistic distances are not evenly spread across this range because there are more unrelated than related language pairs in the world. This was true in our sample of languages too. In fact, the first 25% of distances fell between 0 and .75 while the remaining 75% of distances were concentrated between .75 and .90. To make the spread more homogeneous, we transformed the original distances by raising the power. At the fourth power, the transformed linguistic distances resulted in a more homogeneous spread (quantiles at 0.00, 0.32, 0.41, 0.53, and 0.65). Jäger (2018) proposed that language pairs with distances below .7 should be considered related. Using the transformed linguistic distances, the criterion for related languages became .24 (i.e., .7^4). From here onwards,
(see these linguistic distances in Table S 12).

We also calculated geographic distances for all nation pairs. We used population-weighted centers to reflect the location within each country where participants were most likely to originate. If we could not find population-weighted centers, we used the geographic coordinates of the most populated city of that nation (see Table S13). Using these centers, we calculated distances (in kilometers) on a sphere between all pairs of nations (see Table S14). In two linear regression models, we used linguistic and geographic distances to predict 1) nation-to-nation pattern similarity scores (see Cultural probabilities and their comparisons) Multivariate pattern classification). We argue that comparable results using both approaches provide stronger evidence for the role of linguistic and/or geographic distance, not least because scores are extracted using very different statistical methods correlations and multivariate pattern classification.

Results

Global probabilities

We determined the global matrix of the color-emotion association probabilities based on the unweighted means of the estimated Bayesian probabilities for each color-emotion pair across our 30 nations. Prominent color- , based on our data) were black and sadness, black and fear, black and hate, red and love, red and anger, pink and love, pink and joy, pink and pleasure, grey and sadness, grey and disappointment, yellow and joy, orange and joy, orange and amusement, and white and relief (Fig 3 & Table S 6).

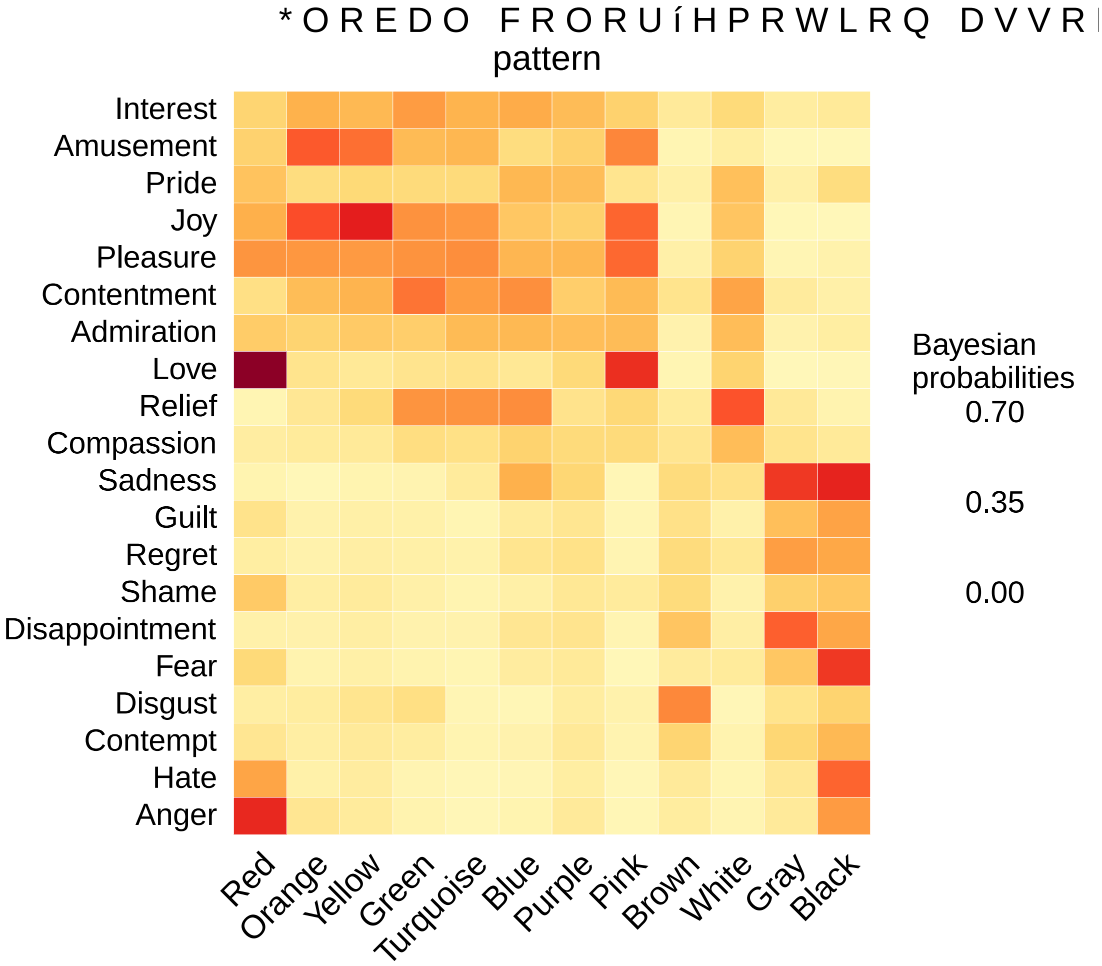

Fig 3. Heatmap of the unweighted averages of the color-emotion association probabilities across our 30 nations. More saturated orange or red indicate a higher probability of a

specific color-emotion association. The cells are not exclusive, meaning that the same participant could have contributed to none, one, or several emotion associations for a given color term (many-to-many associations).

Cultural probabilities

Color-emotion association pattern similarities

The nation-to-global color-emotion association pattern similarities were high and significant for all 30 nations. The average nation-to-global pattern similarity was $r_{average}$ = .880, 95% CI =[.857-.903], p < .001. All nation-to-global pattern similarities ranged from r = .684 (Egypt vs. global) to r = .941 (Spain vs. global), all p-values < .001, FDR corrected (Fig 1 & Fig 4 A). The high pattern similarity indicates that all individual nations associated color terms with emotion concepts similarly to the global pattern. Nation-to-nation pattern similarities were also high and significant (ps < .001). They had a mean of $r_{average}$ = .781, 95%CI = [.773-.789], and ranged from r = .501 (The Netherlands vs. Azerbaijan) to r = .951 (Switzerland vs. France), all p-values < .001, FDR corrected (see Fig S 2, Table S 7). Half of all nation-to-nation correlations fell between .738 and .839, with the median correlation of .799. Fig 4B shows distributions of nation-to-global and nation-to-nation pattern similarities.

Nation-to-global pattern similarities per color term were also high. Average similarities ranged from $r_{average}$ = .659, 95% CI =[.548-.769] (purple) to $r_{average}$ = .925, 95% CI =[.910-.940] (pink) (Fig S3 & Table S 10). Across all nations, purple and yellow had the highest variance in similarities and pink, green, turquoise, and black had the lowest variance in similarities, suggesting that associations with the former colors were the least similar while associations with the latter colors were the most similar across the 30 nations. We also observed certain nation-specific color-emotion associations (Table S 6 & Fig S3). For instance, Nigerians associated red with fear in addition to love and anger; Chinese associated white with sadness in addition to relief. Unlike other nations, Egyptians did not associate joy and other positive emotions with yellow. Greeks associated purple with sadness while other nations, on average, associated purple with positive emotions.

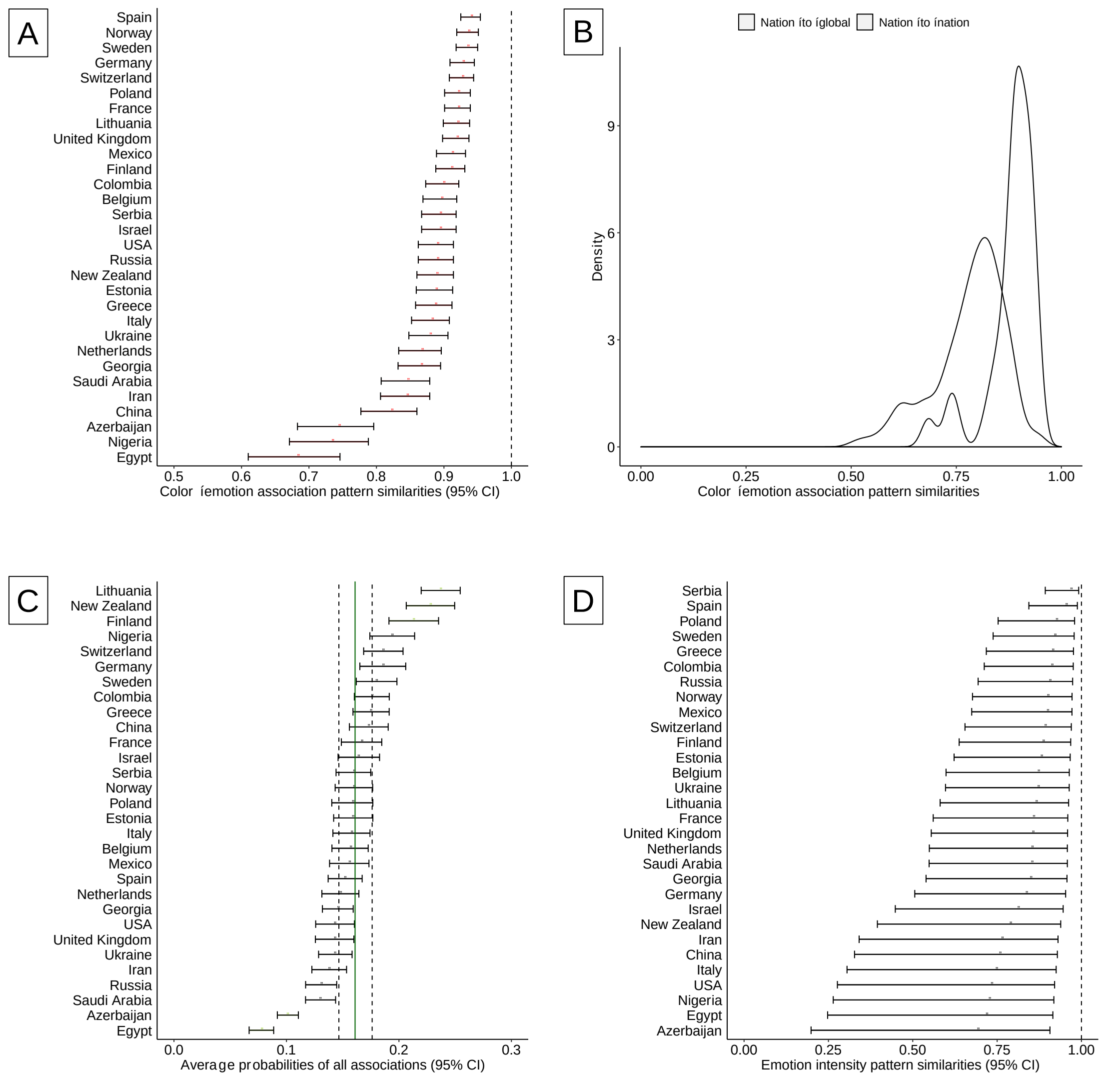

Fig 4. Nation comparisons. (A) Nation-to-global color-emotion association pattern similarities (correlations). The dotted line marks perfect pattern similarity (r = 1). (B) Density plots of nation-to-global and nation-to-nation color-emotion association pattern similarities (correlations). (C) Average probabilities of all color-emotion associations in each nation. The average probability of each nation was compared to the global average probability, which is the unweighted average of all average probabilities (dark green line; grey area = 95% CI). Nations marked in green are significantly different from the global average probability, after FDR correction. A higher score indicates a higher probability of associating any color term with any emotion concept. (D) Nation-to-global emotion intensity pattern similarities (correlations). The dotted line marks perfect pattern similarity (r = 1).

Average probabilities of color-emotion associations

One-sample t-tests showed that the color-emotion association average probabilities were not significantly different from the global average color-emotion association probability in 25 out of 30 nations (Fig 4 C), ps > .604. Only five nations differed significantly from the global average color-emotion association probability. Relative to the global average probability, participants from Finland, Lithuania, and New Zealand were significantly more likely while participants from Azerbaijan and Egypt were significantly less likely to associate color terms with emotion concepts, $ps < .005$, FDR corrected (Fig 4 C, nations in green). When visually inspecting color-emotion association average probabilities per color term (Fig S 4), we found that, in every nation, red and black had the highest and brown the lowest average probability of being associated with any emotion concept.

Emotion intensity pattern similarities

Emotion intensity pattern similarities were high and significant for all 30 nations. The average nation-to-global emotion intensity similarity was $r_{average} = .709$, 95% CI = [.666-.752], $p < .001$, and ranged from $r = .693$ (Azerbaijan vs. global) to $r = .970$ (Serbia vs. global), ps .012, FDR corrected (Fig 4 D).

Multivariate pattern classification

The machine learning classifier correctly predicted the nation for 34.4% of the participants, area under the receiver operating characteristic curve (AUC) = 0.85. This proportion correctly classified instances well above the random guessing rate of 9.7% that can be obtained by always choosing the nation contained most frequently in our data set (Azerbaijan). The AUC of 0.85 was also considerably higher than the AUC for the randomly permuted data sets (0.51). Thus, the classifier performance demonstrates a systematic amount of nation-specificity in color-emotion associations. The confusion matrix (Fig 5) shows that participants from Nigeria were the easiest to predict (true positive rate TPR = .811) while participants from Spain were the most difficult to predict (TPR = .071).

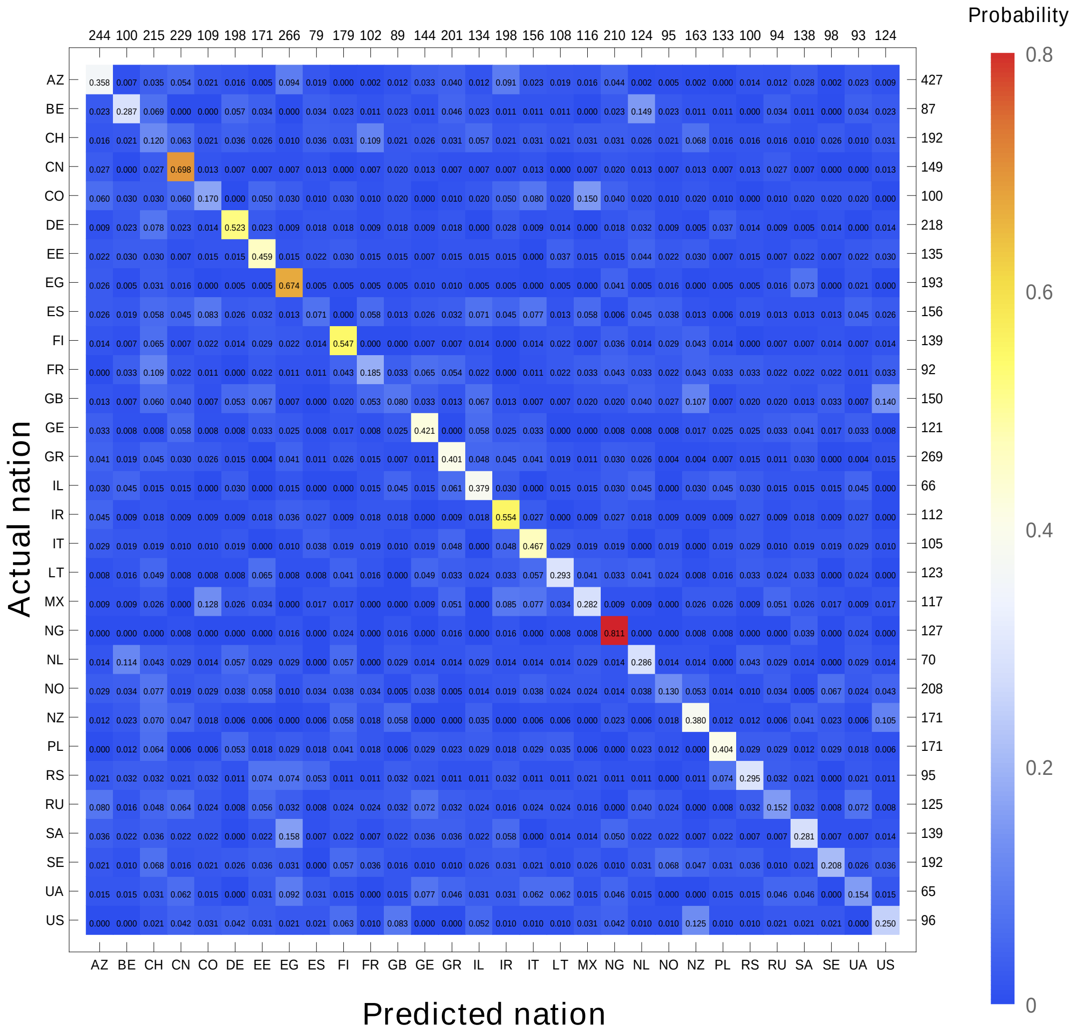

Fig 5
multivariate pattern classification approach). Rows represent the actual and columns the predicted nations, respectively (Table S 1 for nation codes). Cells represent the probability that participants originating from the nations specified in rows were classified by the machine learning algorithm as originating from the nations specified in columns, based on their individual 240 color-emotion associations. Thus, proportions on the main diagonal represent the true positive rate, or recall. The numbers on the right-hand side represent the absolute frequency of participants originating from a given nation. The numbers on the top represent the absolute frequency of participants predicted to originate from a given nation.

Linguistic and geographic distances

We fitted a linear regression model with linguistic and geographic distance measures as predictors of nation-to-nation color-emotion association pattern similarity scores, once with and once without the interaction between the two distance measures. The inclusion of the interaction did not improve the model (p = .389). Therefore, we report the model without the interaction term. The model was overall significant, $F(2, 432) = 39.9$, $p < .001$, and explained 15.2% of variance (adjusted R^2). A shorter linguistic distance, -0.37, $p < .001$, and a shorter geographic distance, -0.13, p = .003, both predicted higher nation-to-nation color-emotion association pattern similarity scores (Fig 6 A&B).

The analogous linear regression model with linguistic and geographic distances as predictors of F(2, 432) = 37.4, p < .001. The model explained 14.4% of variance (adjusted R^2). Again, shorter linguistic, -0.36, p < .001, and geographic distances, -0.13, p = .003, predicted higher similarity scores (Fig 6 C&D).

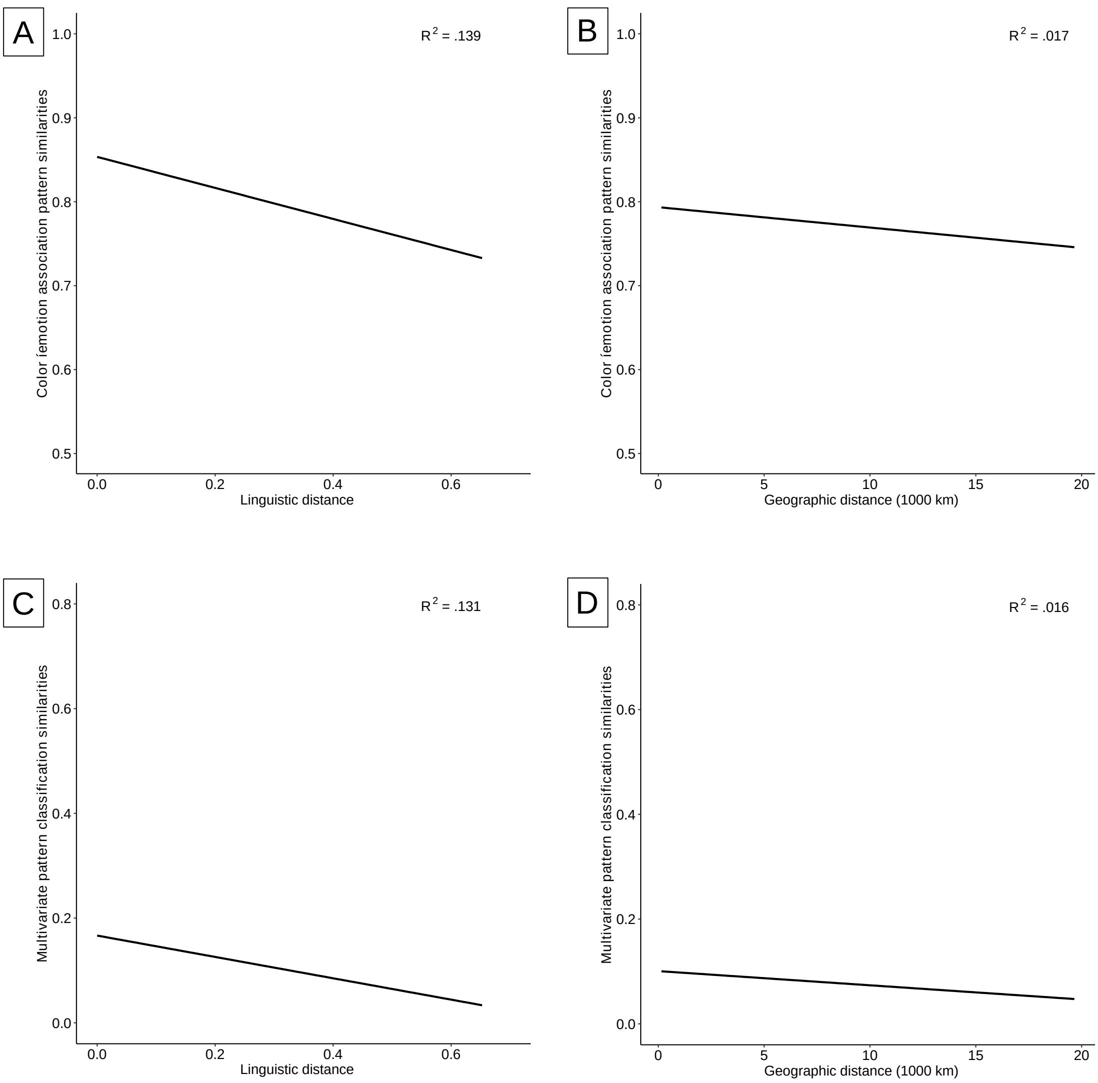

Fig 6. Scatter plots of linguistic and geographic distances predicting nation-to-nation similarities. (A & B) Linguistic and geographic distances predict nation-to-nation association pattern similarities (also see, Fig 4 B & Fig S2). (C & D) Linguistic and geographic distances

model applied to the classifier confusion matrix (multivariate pattern classification similarities; also see Fig S1). Shaded area indicates 95% CI.

Socio-demographic factors

We examined the influence of two key socio-demographic factors sex and age on color-emotion association pattern similarities and on average probabilities of color-emotion associations. Color-emotion association patterns of men and women were almost identical, $r = .987$; $p < .001$ (Table S 8) and there were no age-related pattern differences, $r_{range} = .901$ $.991$; $ps < .001$ (Table S 9). Men and women also did not differ on their average probability of color-emotion associations, $t(478) = 0.49$, $p = .624$ (Fig S 5 A). Notably, however, age was non-linearly related with average probabilities of color-emotion associations. A curve estimation analysis revealed that the association of age with average probabilities followed a U-shaped pattern such that the average probability gradually decreased from early adulthood, that is, from 15-20 years old to 50-60 years old, and then started increasing from 50-60 years of age onwards; $F(2, 1677) = 55.22$, $p < .001$, $R^2_{adj} = .061$ (Fig S 5 B). In other words, 50-60-year-old participants were the least likely to associate any color term with any emotion concept.

Discussion

The cross-modal association of color with emotion is a universal phenomenon. Moreover, there is global similarity in how specific emotion concepts are associated with specific color terms, although these universal associations are modulated by geographic and linguistic factors. Across 30 nations and 22 languages on 6 continents, the pattern of color-emotion associations in each country coincided highly with the global pattern (mean r = .88). In other words, participants from different nations shared the relative tendencies to favor certain color-emotion associations (e.g., love and anger with red) over others (e.g., shame with red). Furthermore, participants from different nations agreed on which colors were the most (i.e., black and red) and the least (i.e., brown) emotional. Finally, they rated emotion intensities in a similar manner. Hence, we demonstrate robust agreement across 30 nations in color-emotion associations, providing strong evidence that such associations might represent a psychological human universal (in agreement with
1974; Gao et al., 2007; Ou et al., 2018). Potential mechanisms for these universal associations may be found in a lasting shared human history, regularities in human languages and environments, and/or shared cognitive biases (Spence, 2011).

But beyond these global similarities, certain color-emotion associations additionally varied locally, (also see Hupka et al., 1997; Madden et al., 2000; Soriano & Valenzuela, 2009). In particular, nations which were linguistically or geographically closer had more similar color-emotion association patterns. Such nations were predicted with lower accuracy by the machine learning algorithm, even though the algorithm could still predict any
nation from the ratings of color-emotion associations above chance level (see also, Jonauskaite, Wicker, et al., 2019). These variations might originate from cultural or linguistic differences in how emotion terms or color terms are understood across nations (Jackson et al., 2019). But these variations might also stem from differences in physical environments themselves. For instance, we have recently reported that exposure to sunshine modulated the degree to which yellow was perceived as a color of joy (Jonauskaite, Abdel-Khalek, et al., 2019).

While the majority of nations did not vary in the extent to which color-emotion associations were endorsed, specific variations were nevertheless observed. Finns, Lithuanians, and New Zealanders endorsed color-emotion associations to a greater extent, while Azerbaijanis and Egyptians did so to a lesser extent than the global average. The source of these differences requires further study. Moreover, some nations exhibited idiosyncratic color-emotion associations. For instance, while sadness was universally associated with black, Greeks also associated it with purple and Chinese also associated it with white. Likely, these divergent color-emotion associations reflect different cultural traditions. White is commonly worn at funerals in China, while Greeks occasionally wear darker shades of purple during mourning periods. Hence, cultural pairings of white, purple, or black with funerals may explain why specific colors are associated with sadness in some nations but not other.

In this study, we asked participants about their associations between color terms and emotion terms, allowing us to capture the conceptual relationship between them (see also, Hupka et al., 1997; Ou et al., 2018; Palmer et al., 2013; Wexner, 1954). However, we do not know if that relationship also plays out in emotional experiences associated with color perception. That is, people may universally associate the concepts of red and anger, but may not universally feel angry when seeing red objects. Within cultures, colors do induce specific subjective and physiological emotional responses (e.g., Wilms & Oberfeld, 2018), and similar emotion concepts are associated with color terms and their best perceptual examples (Jonauskaite et al., 2020). It remains to be seen whether the direct association between color and emotion shows the same patterns of linguistic and geographic modulation we have described here.

Our results suggest there is a universal basis for color-emotion associations, shared by all. Numerous other human universals exist (Brown, 1991). In the domains of color and affect, such universals include but are not limited to the shared understanding of facial emotion expressions (Ekman et al., 1969, but see Gendron et al., 2014), of emotions perceived in music (Cowen et al., 2020), of emotions expressed in human songs (Mehr et al., 2019) and shared loci of focal colors (Regier et al., 2005, but see Uusküla & Bimler, 2016). This universal foundation of color-emotion association is further modulated by language, geography, and culture. Some might understand the modulation as evidence against universality, because color-emotion associations were not shared at 100%. Yet, no human psychological universal is shared at 100% (Mehr et al., 2019; Norenzayan & Heine, 2005; Regier et al., 2005). Gladly, they are not. Scope for dissimilarities seems essential for dynamic adaptations to immediate (Lupyan & Dale, 2016). Others might interpret our overall conclusions as evidence for a globalized world. This concern might be justified, because we mainly tested computer-literate participants who completed the survey online. Potentially, our color-emotion associations become increasingly similar as we share more and more information globally via the Internet and other communication channels. To test the generalizability of our results, we would need further data from small-scale societies (e.g., Davidoff et al., 1999; Groyecka et al., 2019). With our current knowledge at hand, we suggest that color-emotion associations represent a human psychological universal that likely contributes to shared communication and comprehension. Thus, next time you feel blue or see red, know the world is with you.

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Open science statement. The study reported in this article was not formally preregistered. The data can be accessed following this link: https://forsbase.unil.ch/datasets/dataset-public-detail/15126/1474/ and materials following this link: http://www2.unil.ch/onlinepsylab/colour/main.php

References

Adams, F. M., & Osgood, C. E. (1973). A cross-cultural study of the affective meanings of color. Journal of Cross-Cultural Psychology, 4(2), 135 157. https://doi.org/10.1177/002202217300400201

Benitez-Quiroz, C. F., Srinivasan, R., & Martinez, A. M. (2018). Facial color is an efficient mechanism to visually transmit emotion. Proceedings of the National Academy of Sciences, 115(14), 3581 3586. https://doi.org/10.1073/pnas.1716084115

Berlin, B., & Kay, P. (1969). Basic color terms. Their universality and evolution. University of California Press.

Brown, D. (1991). Human universals. McGraw-Hill.

Cowen, A. S., Fang, X., Sauter, D., & Keltner, D. (2020). What music makes us feel: At least 13 dimensions organize subjective experiences associated with music across different cultures. Proceedings of the National Academy of Sciences, 117(4), 1924 1934. https://doi.org/10.1073/pnas.1910704117

American Ethnologist, 1(1), 49 63. https://doi.org/10.1525/ae.1974.1.1.02a00030

Davidoff, J. B., Davies, I., & Roberson, D. (1999). Colour categories in a stone-age tribe. Nature, 398(6724), 203 204. https://doi.org/10.1038/18335

Dietterich, T. G., & Bakiri, G. (1995). Solving multiclass learning problems via error-correcting output codes. Journal of Artificial Intelligence Research, 2, 263 286. https://doi.org/10.1613/jair.105

Ekman, P., Sorenson, E. R., & Friesen, W. V. (1969). Pan-cultural elements in facial displays of emotion. Science, 164(3875), 86 88. https://doi.org/10.1126/science.164.3875.86

Evarts, A. B. (1919). Color symbolism. The Psychoanalytic Review, 6(2), 124 157.

Gao, X., Xin, J. H., Sato, T., Hansuebsai, A., Scalzo, M., Kajiwara, K., Guan, S., Valldeperas, J., Lis, M. J., & Billger, M. (2007). Analysis of cross-cultural color emotion. Color Research & Application, 32(3), 223 229. https://doi.org/10.1002/col.20321

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. Statistical Science, 7(4), 457 472. https://www.jstor.org/stable/2246093

Gendron, M., Roberson, D., van der Vyver, J. M., & Barrett, L. F. (2014). Perceptions of emotion from facial expressions are not culturally universal: Evidence from a remote culture. Emotion, 14(2), 251 262. https://doi.org/10.1037/a0036052

Good, P. (2005). Permutation, Parametric, and Bootstrap Tests of Hypotheses (3rd ed.). Springer.

Groyecka, A., Witzel, C., Butovskaya, M., & Sorokowski, P. (2019). Similarities in color preferences between women and men: The case of Hadza, the hunter-gatherers from Tanzania. Perception, 48(5), 428 436. https://doi.org/10.1177/0301006619840937

Hupka, R. B., Zaleski, Z., Otto, J., Reidl, L., & Tarabrina, N. V. (1997). The colors of anger, envy, fear, and jealousy. Journal of Cross-Cultural Psychology, 28(2), 156 171. https://doi.org/10.1177/0022022197282002

Jackson, J. C., Watts, J., Henry, T. R., List, J.-M., Forkel, R., Mucha, P. J., Greenhill, S. J., Gray, R. D., & Lindquist, K. A. (2019). Emotion semantics show both cultural variation and universal structure. Science, 366(6472), 1517 1522. https://doi.org/10.1126/science.aaw8160

Jäger, G. (2018). Global-scale phylogenetic linguistic inference from lexical resources. Scientific Data, 5(1), 180189. https://doi.org/10.1038/sdata.2018.189

Jonauskaite, D., Abdel-Khalek, A. M., Abu-Akel, A., Al-Rasheed, A. S., Antonietti, J.-P., Ásgeirsson, Á. G., Atitsogbe, K. A., Barma, M., Barratt, D., Bogushevskaya, V., Bouayed Meziane, M. K., Chamseddine, A., Charernboom, T., Chkonia, E., Ciobanu, T., Corona, V.,

environments affect how we feel about yellow across 55 countries. Journal of Environmental Psychology, 66, 101350. https://doi.org/10.1016/j.jenvp.2019.101350

Jonauskaite, D., Parraga, C. A., Quiblier, M., & Mohr, C. (2020). Feeling blue or seeing red? Similar patterns of emotion associations with colour patches and colour terms. I-Perception, 11(1), 1 24. https://doi.org/10.1177/2041669520902484

Jonauskaite, D., Wicker, J., Mohr, C., Dael, N., Havelka, J., Papadatou-Pastou, M., Zhang, M., & Oberfeld, D. (2019). A machine learning approach to quantify the specificity of colour emotion associations and their cultural differences. Royal Society Open Science, 6(9), 190741. https://doi.org/10.1098/rsos.190741

Lee, M. D., & Wagenmakers, E.-J. (2013). Bayesian Cognitive Modeling: A Practical Course. Cambridge University Press.

Luce, R. D. (1963). Detection and recognition. In R. D. Luce, R. R. Bush, & E. Galanter (Eds.), Handbook of Mathematical Psychology, Vol. I (pp. 103 189). Wiley.

Lupyan, G., & Dale, R. (2016). Why are there different languages? The role of adaptation in linguistic diversity. Trends in Cognitive Sciences, 20(9), 649 660. https://doi.org/10.1016/j.tics.2016.07.005

Madden, T. J., Hewett, K., & Roth, M. S. (2000). Managing images in different cultures: A cross-national study of color meanings and preferences. Journal of International Marketing, 8(4), 90 107. https://doi.org/10.1509/jimk.8.4.90.19795

Major, D. R. (1895). On the affective tone of simple sense-impressions. The American Journal of Psychology, 7(1), 57 77. https://www.jstor.org/stable/1412037

Mehr, S. A., Singh, M., Knox, D., Ketter, D. M., Pickens-Jones, D., Atwood, S., Lucas, C., Jacoby, N., Egner, A. A., Hopkins, E. J., Howard, R. M., Hartshorne, J. K., Jennings, M. V, Simson,

Universality and diversity in human song. Science, 366(6468), eaax0868. https://doi.org/10.1126/science.aax0868

Mohr, C., Jonauskaite, D., Dan-Glauser, E. S., Uusküla, M., & Dael, N. (2018). Unifying research on colour and emotion: Time for a cross-cultural survey on emotion associations with colour terms. In L. W. MacDonald, C. P. Biggam, & G. V Paramei (Eds.), Progress in colour studies: Cognition, language, and beyond (pp. 209 222). John Benjamins Publishing Company. https://doi.org/10.1075/z.217.11moh

Mylonas, D., & MacDonald, L. (2015). Augmenting basic colour terms in English. Color Research and Application, 41(1), 32 42. https://doi.org/10.1002/col.21944

Norenzayan, A., & Heine, S. J. (2005). Psychological universals: What are they and how can we know? Psychological Bulletin, 131(5), 763 784. https://doi.org/10.1037/0033-2909.131.5.763

Ou, L. C., Yuan, Y., Sato, T., Lee, W. Y., Szabó, F., Sueeprasan, S., & Huertas, R. (2018). Universal models of colour emotion and colour harmony. Color Research and Application, 43(5), 736 748. https://doi.org/10.1002/col.22243

Palmer, S. E., Schloss, K. B., Xu, Z., & Prado-Leon, L. R. (2013). Music-color associations are mediated by emotion. Proceedings of the National Academy of Sciences, 110(22), 8836 8841. https://doi.org/10.1073/pnas.1212562110

Platt, J. (1998). Fast training of support vector machines using sequential minimal optimization. In B. Schoelkopf, C. Burges, & A. Smola (Eds.), Advances in Kernel Methods - Support Vector Learning (pp. 41 65). MIT Press.

Pravossoudovitch, K., Cury, F., Young, S. G., & Elliot, A. J. (2014). Is red the colour of danger? Testing an implicit red danger association. Ergonomics, 57(4), 503 510. https://doi.org/10.1080/00140139.2014.889220

Regier, T., Kay, P., & Cook, R. S. (2005). Focal colors are universal after all. Proceedings of the National Academy of Sciences, 102(23), 8386 8391. https://doi.org/10.1073/pnas.0503281102

Scherer, K. R. (2005). What are emotions? And how can they be measured? Social Science Information, 44(4), 695 729. https://doi.org/10.1177/0539018405058216

Scherer, K. R., Shuman, V., Fontaine, J. R. J., & Soriano, C. (2013). The GRID meets the Wheel: Assessing emotional feeling via self-report. In J. R. J. Fontaine, K. R. Scherer, & C. Soriano (Eds.), Components of emotional meaning: A sourcebook (pp. 281 298). Oxford University Press. https://doi.org/10.13140/RG.2.1.2694.6406

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. Psychological Science, 22(11), 1359 1366. https://doi.org/10.1177/0956797611417632

Soriano, C., & Valenzuela, J. (2009). Emotion and colour across languages: implicit associations in Spanish colour terms. Social Science Information, 48(3), 421 445. https://doi.org/10.1177/0539018409106199

Spence, C. (2011). Crossmodal correspondences: A tutorial review. Attention, Perception, and Psychophysics, 73(4), 971 995. https://doi.org/10.3758/s13414-010-0073-7

Uusküla, M., & Bimler, D. (2016). How universal are focal colors after all? A new methodology for identifying focal color terms. In G. Paulsen, M. Uusküla, & J. Brindle (Eds.), Color language and color categorization (pp. 2 39). Cambridge Scholars Publishing.

Valdez, P., & Mehrabian, A. (1994). Effects of color on emotions. Journal of Experimental Psychology: General, 123(4), 394 409. https://doi.org/10.1037/0096-3445.123.4.394

van Ravenzwaaij, D., Cassey, P., & Brown, S. D. (2018). A simple introduction to Markov Chain Monte Carlo sampling. Psychonomic Bulletin & Review, 25(1), 143 154. https://doi.org/10.3758/s13423-016-1015-8

Venables, W. N., & Ripley, B. D. (2002). Modern Applied Statistics with S (Statistics and Computing) (4th ed.). Springer.

Wang, T., Shu, S., & Mo, L. (2014). Blue or red? The effects of colour on the emotions of Chinese people. Asian Journal of Social Psychology, 17(2), 152 158. https://doi.org/10.1111/ajsp.12050

Wexner, L. B. (1954). The degree to which colors (hues) are associated with mood-tones. Journal of Applied Psychology, 38(6), 432 435. https://doi.org/10.1037/h0062181

Wilms, L., & Oberfeld, D. (2018). Color and emotion: effects of hue, saturation, and brightness. Psychological Research, 82(5), 896 914. https://doi.org/10.1007/s00426-017-0880-8

Supplementary material

Supplementary method details

Translation of the Geneva Emotion Wheel. The English, Dutch, Estonian, Finnish, French, German, Italian, Traditional Mandarin Chinese, and Polish versions of the Geneva Emotion Wheel are available from the Swiss Centre for Affective Sciences (http://www.affective-sciences.org/gew
https://www.affective-sciences.org/research/topics/specific-research-projects/language-and-culture/grid-project/emotion-words/). For all other nations, our collaborators and co-authors translated the Geneva Emotion Wheel into their respective national languages (i.e., Arabic, Azerbaijani, Georgian, Greek, Hebrew, Lithuanian, Norwegian, Persian, Russian, Serbian, Simplified Mandarin Chinese, Spanish, Swedish, and Ukrainian; see Table S 3 for the emotion concepts in all languages). To ensure that the meaning of the translated emotion concepts was as close as possible to the meaning of the original emotion concepts, we followed the back-translation technique. Following this technique, one translator (a bilingual person in the target and reference language) translated the emotion concepts into the target language. Then, the second translator (a bilingual person in the target and reference language) translated the emotion concepts from the target to the reference language without knowing the original reference version. Then, the two versions the reference and the back translated version were compared, and the discrepancies were resolved through discussion and consultation of dictionaries. Although we cannot guarantee that the original meaning of the emotion terms remained unchanged in the translations (similar concerns were expressed in Adams & Osgood, 1973), all efforts were made to bring the translations as close as possible to the original meaning, and as similar as possible across languages.

Bayesian probabilities. We constructed Bayesian models with Monte-Carlo Markov Chains (MCMC) to estimate the average probability that participants associated each emotion concept with the given color term (Lee & Wagenmakers, 2013). The Bayesian method consists of comparing an a-priori distribution of the probabilities of parameter values (without taking into account the data, i.e., the prior distribution) with a posterior distribution (when taking into account the data). The parameter values were 240 color-emotion associations.
e given
color term (irrespective of emotion intensity), and 0 if an emotion was not associated with the given color term, and were fitted to a Bernoulli distribution.

We used a uniform prior distribution, which provides a neutral and un-biased starting point, due to the lack of more informative priors in the literature. The uniform distribution assumes that each emotion parameter value (between 0 and 1) is equally probable across all participants for a given color term. We constructed the posterior distribution using the MCMC method with 10,000 iterations and three chains (thinning interval was 1). We used a JAGS code to generate three MCMC chains, each comprised of 10,000 iterations. After discarding the first 5,000 iterations from each chain burn-in and confirming convergence by visual inspection and the statistic (Gelman & Rubin, 1992), we collapsed the samples across the three chains so that our inference was based on a total of 30,000 samples from the joint posterior. MCMC is a computer-driven sampling method that efficiently produces samples from a probability distribution that is otherwise difficult to sample from directly (van Ravenzwaaij et al., 2018).
(Venables & Ripley, 2002)

Multivariate pattern classification. Only participants who had provided ratings for all of the 240 color-emotion associations were included in the analysis (N = 4410). For the classification algorithm, we selected a support vector machines (SVM; (Platt, 1998)) with a radial basis function (RBF) kernel, and used error-correcting output codes (ECOC) for the multiclass classification (Dietterich & Bakiri, 1995). To optimize the hyperparameters of the SVM (complexity constant C -parameter of the RBF kernel), we used Bayesian optimization based on 5-fold cross validation. Because the sample sizes differed between our 30 nations, we used a uniform prior when training and evaluating the classifier, so that the results were not affected by the differing prior probabilities of the 30 classes (i.e., nations). To evaluate the accuracy of the classifier, a ten-fold cross-validation (CV) was conducted. The analyses were implemented in Matlab (function fitcecoc). A summary measure of the predictive power of a classifier is the area under the receiver operating characteristic (ROC) curve (AUC). This measure provides information about the degree to which the predicted nation is concordant with the actual nation. Areas of 0.5 and 1.0 correspond to performances at chance level and perfect performance of the classifier, respectively. AUC is not affected by response bias or by prior probabilities of the classes.

We compared the performance of the classifier to the performance of the same method on randomized data sets. The randomized data sets were generated by randomly permuting the class values (i.e., nation labels) of the data set (Good, 2005).

Linguistic distances. We have included the following languages from Jäger (2018) in our analyses: AZERBAIJANI_NORTH_2, DUTCH, ENGLISH, ESTONIAN, FINNISH, FRENCH, GEORGIAN, GREEK, HEBREW, ITALIAN, LITHUANIAN, MANDARIN, NORWEGIAN_BOKMAAL, PERSIAN, POLISH, RUSSIAN, SERBOCROATIAN, SPANISH, STANDARD_ARABIC, STANDARD_GERMAN, SWEDISH, and UKRAINIAN.

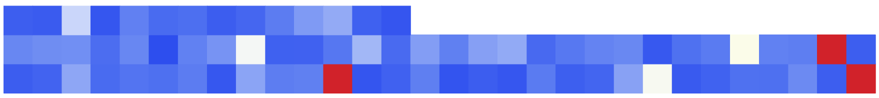

Fig S 1
model applied to the classifier confusion matrix. Similarity is coded on a temperature scale ranging from blue (0, no similarity) to red (1, perfect similarity). Nation codes are available in Table S 1.